Imports

In [3]:

```
#Plot
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

#Data Packages
import math
import pandas as pd
import numpy as np

#Progress bar
from tqdm import tqdm

#Counter
from collections import Counter

#Operation
import operator

#Natural Language Processing Packages
import re
import nltk

## Download Resources
nltk.download("vader_lexicon")
nltk.download("stopwords")
nltk.download("averaged_perceptron_tagger")
nltk.download("wordnet")

from nltk.sentiment import SentimentAnalyzer
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.sentiment.util import *
from nltk import tokenize
from nltk.tokenize import RegexpTokenizer
from nltk.stem import WordNetLemmatizer
from nltk.stem.snowball import SnowballStemmer
from nltk.corpus import stopwords
from nltk.tag import PerceptronTagger
from nltk.data import find

## Machine Learning
import sklearn
import sklearn.metrics as metrics
```

```
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Load Data

In [4]:

```
hotelDf = pd.read_csv('reviews.csv')
hotelDf.columns=['filePath','hotelName','reviewColumn','ratingScore','groundTruth']
hotelDf['reviewColumn'] = hotelDf['reviewColumn'].fillna("no")
hotelDf.drop(['filePath'],axis=1,inplace=True)
hotelDf.head(3)
```

Out[4]:

	hotelName	reviewColumn	ratingScore	groundTruth
0	Holiday Inn Express Hotel & Suites Kingston	"We stayed here just passing through on our wa...	5	positive
1	Holiday Inn Express Hotel & Suites Kingston	"I travel frequently for business and Kingston...	4	positive
2	Holiday Inn Express Hotel & Suites Kingston	"We were in town for a sporting event, so we o...	4	positive

Q1

In [0]:

```
def sentiment_scores(sentence):

    # Create a SentimentIntensityAnalyzer object.
    sid_obj = SentimentIntensityAnalyzer()

    # polarity_scores method of SentimentIntensityAnalyzer
    # oject gives a sentiment dictionary.
    # which contains pos, neg, neu, and compound scores.
    sentiment_vader = sid_obj.polarity_scores(sentence)['compound']
    return sentiment_vader
```

In [6]:

```
hotelDf['vader'] = hotelDf['reviewColumn'].apply(sentiment_scores)
hotelDf.head()
```

Out[6]:

	hotelName	reviewColumn	ratingScore	groundTruth	vader
0	Holiday Inn Express Hotel & Suites Kingston	"We stayed here just passing through on our wa...	5	positive	0.9931
1	Holiday Inn Express Hotel & Suites Kingston	"I travel frequently for business and Kingston...	4	positive	0.9910
2	Holiday Inn Express Hotel & Suites Kingston	"We were in town for a sporting event, so we o...	4	positive	0.8581
3	Holiday Inn Express Hotel & Suites Kingston	"My parents had a car accident this weekend ne...	5	positive	-0.5538
4	Holiday Inn Express Hotel & Suites Kingston	"The room was very nice. Place is clean and m...	5	positive	0.9440

(a) Compute average Vader sentiment and average ground truth rating per hotel.

In [7]:

```
hotel_avgDF = hotelDf.groupby('hotelName')['ratingScore','vader'].mean().reset_index()
hotel_avgDF.head()
```

Out[7]:

	hotelName	ratingScore	vader
0	A Cherry Place Bed and Breakfast	4.950000	0.960145
1	All Suites Whitney Manor	4.858824	0.881452
2	Ambassador Hotel & Conference Centre	3.380000	0.433337
3	Bayside Inn & Waterfront Suites	2.700000	0.249661
4	Best Western Fireside Inn	4.550000	0.849882

(b) List ranked hotels

In [0]:

```
hotelNames = hotel_avgDF['hotelName'].unique()
```

In [0]:

```
def getHotelRank(df, measure='ratingScore'):
    #Rank the hotel by ground truth rating score
    hotelRating = []
    for hotel in hotelNames:
        itemDf = df.loc[df['hotelName']==hotel]
        hotelRating.append([hotel,itemDf[measure].mean()])
    hotelRatingDfGt = pd.DataFrame(hotelRating)
    hotelRatingDfGt.columns=['hotelName','avgRatingScore']
    hotelRatingDfGt = hotelRatingDfGt.sort_values('avgRatingScore',ascending=0)
    return hotelRatingDfGt
```

In [0]:

```
hotelRatingDfGt = getHotelRank(hotel_avgDF)
hotelRatingDfVd = getHotelRank(hotel_avgDF, measure='vader')
```

In [11]:

```
hotelRatingDfVd.head(5)
```

Out[11]:

	hotelName	avgRatingScore
0	A Cherry Place Bed and Breakfast	0.960145
18	Green Woods Inn	0.959917
34	Secret Garden Bed & Breakfast Inn	0.954265
17	Green Acres Inn	0.926452
40	The Rosemount Inn	0.898553

In [13]:

```
hotelRatingDfGt.head(5)
```

Out[13]:

	hotelName	avgRatingScore
18	Green Woods Inn	4.962963
0	A Cherry Place Bed and Breakfast	4.950000
1	All Suites Whitney Manor	4.858824
34	Secret Garden Bed & Breakfast Inn	4.762500
17	Green Acres Inn	4.620000

In [12]:

```
hotelRatingDfVd.tail(5)
```

Out[12]:

	hotelName	avgRatingScore
32	Ramada by Wyndham Kingston Hotel and Conferenc...	0.280141
26	Knights Inn Kingston	0.273062
3	Bayside Inn & Waterfront Suites	0.249661
14	Fort Henry Motel	0.239760
43	Welcome Traveller Motel	0.183920

In [14]:

```
hotelRatingDfGt.tail(5)
```

Out[14]:

	hotelName	avgRatingScore
26	Knights Inn Kingston	2.886792
3	Bayside Inn & Waterfront Suites	2.700000
43	Welcome Traveller Motel	2.500000
16	General Wolfe Hotel	2.333333
27	Kozy Inn	2.133333

The top 5 and bottom 5 for both ranking methods agree well. Top 5 have 4 same hotels with a little different ranking order. As for the bottom 5 hotels, 3 of them are in both ranking metrics with the same ranking order.

Q2. Frequency Analysis

(a) term frequency for non-stopwords

In [0]:

```
def non_stopword(df, label='all',k=50):
  if label=='all':
    reviews = df['reviewColumn'].values
  else:
    reviews = df[df['groundTruth']==label]['reviewColumn'].values
  stop = set(stopwords.words('english'))
  stop.add('hotel')
  stop.add('room')
  stop.add('rooms')
  stop.add('stay')
  stop.add('staff')
  stop.add('kingston')
  # Top-k frequent terms
  counter = Counter()
  tokenizer = RegexpTokenizer(r'\w+')
  lemmatizer = WordNetLemmatizer()
  stemer=nltk.stem.porter.PorterStemmer()
  for review in reviews:
      words = [i  for i in tokenizer.tokenize(review.lower()) if i not in stop and len(i)>2]
      counter.update(words)
  topk = counter.most_common(k)
  return topk
```

In [0]:

```
top50_pos_word=non_stopword(hotelDf,label='positive')
top50_neg_word=non_stopword(hotelDf,label='negative')
```

In [17]:

```
print("Top50 frequent words in positive reviews:")
print([word[0] for word in top50_pos_word])
print("Top50 frequent words in negative reviews:")
print([word[0] for word in top50_neg_word])
```

```
Top50 frequent words in positive reviews:
['clean', 'breakfast', 'great', 'good', 'nice', 'comfortable', 'friendly', 'woul
d', 'stayed', 'well', 'place', 'one', 'bed', 'inn', 'night', 'area', 'location',
'downtown', 'helpful', 'nthe', 'time', 'parking', 'coffee', 'also', 'back', 'clos
e', 'like', 'quiet', 'motel', 'recommend', 'beds', 'restaurants', 'front', 'servic
e', 'really', 'bathroom', 'everything', 'right', 'lovely', 'little', 'two', 'get',
'could', 'check', 'definitely', 'next', 'excellent', 'pool', 'desk', 'small']
Top50 frequent words in negative reviews:
['would', 'breakfast', 'night', 'one', 'clean', 'good', 'bed', 'could', 'place',
'desk', 'nthe', 'stayed', 'like', 'get', 'front', 'bathroom', 'parking', 'locatio
n', 'door', 'back', 'time', 'nice', 'inn', 'two', 'also', 'check', 'small', 'tol
d', 'floor', 'well', 'even', 'coffee', 'friendly', 'great', 'motel', 'old', 'firs
t', 'dirty', 'price', 'comfortable', 'booked', 'beds', 'morning', 'day', 'next',
'water', 'really', 'little', 'people', 'service']
```

Both top50 words in positive and negative reviews contain some same nouns such as breakfast, bed, location, etc.

In positive reviews, most adjectives are positive such as clean, great,comfortable,friendly. Interestingly, some of the frequent adjectives in negative reviews are also positive. It's maybe because these words are negated (e.g."not clean","not good").

(b) term frequency for noun phrases

In [0]:

```
# Noun Phrase Extraction Support Functions
# generator, generate leaves one by one
def leaves(tree):
    """Finds NP (nounphrase) leaf nodes of a chunk tree."""
    for subtree in tree.subtrees(filter = lambda t: t.label()=='NP' or t.label()=='JJ' or t.la
bel()=='RB'):
        yield subtree.leaves()

# stemming, lematizing, lower case...
def normalise(word):
    """Normalises words to lowercase and stems and lemmatizes it."""
    word = word.lower()
    word = nltk.stem.porter.PorterStemmer().stem(word)
    word = nltk.WordNetLemmatizer().lemmatize(word)
    return word
# stop-words and length control
def acceptable_word(word):
    """Checks conditions for acceptable word: length, stopword."""
    accepted = bool(2 <= len(word) <= 40
        and word.lower() not in stopwords.words('english'))
    return accepted
# generator, create item once a time
def get_terms(tree):
    for leaf in leaves(tree):
        term = [normalise(w) for w,t in leaf if acceptable_word(w)]
        # Phrase only
        if len(term)>1:
            yield term
# Flatten phrase lists to get tokens for analysis
def flatten(npTokenList):
    finalList =[]
    for phrase in npTokenList:
        token = ''
        for word in phrase:
            token += word + ' '
        finalList.append(token.rstrip())
    return finalList
```

In [0]:

```
def NP_topk(df, label='all',k=50):
  if label=='all':
    reviews = df['reviewColumn'].values
  else:
    reviews = df[df['groundTruth']==label]['reviewColumn'].values
  grammar = r"""
    NBAR:
        {<NN.*|JJ>*<NN.*>}  # Nouns and Adjectives, terminated with Nouns

    NP:
        {<NBAR>}
        {<NBAR><IN><NBAR>}  # Above, connected with in/of/etc...
    """
    # Create phrase tree
  chunker = nltk.RegexpParser(grammar)
  tagger = PerceptronTagger()
  pos_tag = tagger.tag
  tokenizer = RegexpTokenizer(r'\w+')
  # Top-k frequent terms
  counter = Counter()
  for review in reviews:
          counter.update(flatten([word
                          for word
                          in get_terms(chunker.parse(pos_tag(tokenizer.tokenize(review))))
                          ]))
  topk = counter.most_common(k)
  return topk
```

In [0]:

```
top50_pos_NP = NP_topk(hotelDf,label='positive')
top50_neg_NP = NP_topk(hotelDf,label='negative')
```

In [21]:

```
print("Top50 frequent noun phrases in positive reviews:")
print([word[0] for word in top50_pos_NP])
print("\nTop50 frequent noun phrases in negative reviews:")
print([word[0] for word in top50_neg_NP])
```

```
Top50 frequent noun phrases in positive reviews:
['front desk', 'downtown kingston', 'comfort bed', 'great place', 'night stay', 'f
riendli staff', 'front desk staff', 'kingston area', 'minut drive', 'nthe room',
'great locat', 'good valu', 'next time', 'hot tub', 'clean room', 'secret garden',
'hotel room', 'great stay', 'coffe maker', 'nice touch', 'tim horton', 'free break
fast', 'whitney manor', 'nice place', 'short walk', 'park lot', 'good night', 'fir
st time', 'queen univers', 'comfort inn', 'good locat', 'next door', 'next morn',
'nice hotel', 'queen bed', 'nthe staff', 'short drive', 'continent breakfast', 'mi
nut walk', 'great restaur', 'small fridg', 'lake ontario', 'hochelaga inn', 'easi
access', 'comfort room', 'downtown area', 'great valu', 'great view', 'green acr i
nn', 'great hotel']

Top50 frequent noun phrases in negative reviews:
['front desk', 'comfort inn', 'credit card', 'park lot', 'holiday inn', 'first nig
ht', 'queen bed', 'great locat', 'front desk staff', 'hot tub', 'nthe room', 'cont
inent breakfast', 'air condition', 'next time', 'good thing', 'next morn', 'free b
reakfast', 'next day', 'bathroom door', 'ground floor', 'night stay', 'mini frid
g', 'doubl bed', 'breakfast room', 'hot water', 'hotel staff', 'king room', 'secon
d night', 'tim horton', 'hotel room', 'non smoke room', 'long time', 'second floo
r', 'custom servic', 'good locat', 'first room', 'toilet paper', 'clean staff', 'n
the bed', 'free wifi', 'pool area', 'mani hotel', 'first time', 'princess street',
'best western', 'next door', 'nice place', 'last time', 'good clean', 'nthe breakf
ast']
```

Similarly, frequent noun phrase in positive reviews includes most of postive words, like comfort bed, friendli staff, and locate-specific phrase like short walk, great locat, downtown kingston.

From the negative reives, some complaints can be concluded since it contains most of facility phrases such as air condition, bathroom door, mini fridg...

Q3. Mutual Information

In [0]:

```
def comprehensiveDf(df, topK,mode):
    reviews = df['reviewColumn'].values
    tokenizer = RegexpTokenizer(r'\w+')
    freqReview = []
    if mode == 'word':
        for review in reviews:
            tempCounter = Counter([word.lower() for word in tokenizer.tokenize(review)])
            topkinReview = [1 if tempCounter[word] > 0 else 0 for (word,wordCount) in topK]
            freqReview.append(topkinReview)
    elif mode=='phrase':
        grammar = r"""
            NBAR:
                {<NN.*|JJ>*<NN.*>}  # Nouns and Adjectives, terminated with Nouns
            NP:
                {<NBAR>}
                {<NBAR><IN><NBAR>}  # Above, connected with in/of/etc...
        """
        chunker = nltk.RegexpParser(grammar)
        tagger = PerceptronTagger()
        pos_tag = tagger.tag
        for review in reviews:
            tempCounter = Counter(flatten([word
                                           for word
                                           in get_terms(chunker.parse(pos_tag(tokenizer.tokenize
(review))))]))
            topkinReview = [1 if tempCounter[word] > 0 else 0 for (word,wordCount) in topK]
            freqReview.append(topkinReview)

    #Find out if a particular review has the word from topk list
    for review in reviews:
        tempCounter = Counter([word for word in tokenizer.tokenize(review.lower())])
        topkinReview = [1 if tempCounter[word] > 0 else 0 for (word,wordCount) in topK]
        freqReview.append(topkinReview)

    #Prepare freqReviewDf
    freqReviewDf = pd.DataFrame(freqReview)
    dfName = []

    freqReviewDf.columns = [c[0] for c in topK]
    finalreviewDf = df.join(freqReviewDf)
    return finalreviewDf
```

In [0]:

```
# get Top K mutual information terms from the dataframe
def getMI(topk, df, label_column='groundTruth'):
    miScore = []
    for word in topk:
        miScore.append([word[0]]+[metrics.mutual_info_score(df[label_column], df[word[0]])])
    miScoredf = pd.DataFrame(miScore).sort_values(1,ascending=0)
    miScoredf.columns = ['Word','MI Score']
    return miScoredf
```

(a) Mutual Information(Word)

In [0]:

```
topk_word=non_stopword(hotelDf,label='all')
finaldf = comprehensiveDf(hotelDf,topk_word,mode='word')
miScoredf = getMI(topk_word, finaldf)
```

In [55]:

```
miScoredf.head(50)
```

Out[55]:

	Word	MI Score
4	great	0.022961
7	comfortable	0.019327
0	clean	0.015937
48	door	0.014776
29	downtown	0.013517
10	friendly	0.012464
21	could	0.011975
32	helpful	0.010858
47	quiet	0.009458
9	night	0.009065
49	restaurants	0.009035
25	get	0.007871
6	one	0.007719
26	desk	0.007608
5	nice	0.006018
27	bathroom	0.005254
19	like	0.005082
13	well	0.004808
18	area	0.004603
46	even	0.004239
45	recommend	0.003909
22	front	0.003372
41	price	0.002514
2	would	0.002305
16	nthe	0.002150
35	small	0.002139
34	check	0.002068
1	breakfast	0.001540
36	close	0.001508
23	back	0.001165
31	two	0.000831
8	stayed	0.000766
17	parking	0.000749

	Word	MI Score
44	right	0.000659
24	also	0.000482
20	time	0.000444
40	next	0.000325
12	bed	0.000261
3	good	0.000238
42	day	0.000175
15	location	0.000112
39	little	0.000109
14	inn	0.000105
37	really	0.000101
30	motel	0.000083
11	place	0.000029
33	beds	0.000017
43	pool	0.000015
28	coffee	0.000007
38	service	0.000003

The list contains both postive and negative reviews, so it is hard to determine the noun is a complaint or a praise. The adjectives are mostly postive.

(b) Mutual Information(Noun Phrase)

In [57]:

```
topk_np=NP_topk(hotelDf,label='all')
finaldf_np = comprehensiveDf(hotelDf,topk_np,mode='phrase')
miScoredf_np = getMI(topk_np, finaldf_np)
miScoredf_np.head(50)
```

Out[57]:

	Word	MI Score
0	front desk	0.007252
23	credit card	0.005241
29	first night	0.003853
17	holiday inn	0.002498
2	downtown kingston	0.002176
14	friendli staff	0.002154
1	comfort inn	0.002137
6	park lot	0.001988
38	great stay	0.001982
11	great place	0.001922
4	comfort bed	0.001832
21	kingston area	0.001765
43	whitney manor	0.001761
22	minut drive	0.001671
35	secret garden	0.001543
41	air condition	0.001542
46	next day	0.001517
34	nice touch	0.001431
48	breakfast room	0.001297
42	ground floor	0.001157
45	mini fridg	0.001157
49	nthe staff	0.000706
44	hot water	0.000661
18	continent breakfast	0.000603
31	short walk	0.000595
39	hotel staff	0.000459
20	next morn	0.000435
28	coffe maker	0.000392
32	good night	0.000392
33	queen univers	0.000392
47	minut walk	0.000336
15	good valu	0.000308
12	queen bed	0.000306

	Word	MI Score
24	clean room	0.000297
7	great locat	0.000204
9	hot tub	0.000122
8	nthe room	0.000115
13	free breakfast	0.000099
37	short drive	0.000047
25	nice place	0.000033
36	pool area	0.000032
10	next time	0.000030
5	night stay	0.000022
27	first time	0.000018
26	good locat	0.000016
3	front desk staff	0.000009
19	tim horton	0.000006
40	princess street	0.000004
30	next door	0.000001
16	hotel room	0.000001

We can see that no matter the review is positive or negative , most tourists care about the front desk service most.

Q4. Pointwise Mutual Information

In [0]:

```
def pmiCal(df, x):
    pmilist=[]
    for i in ['positive','negative']:
        for j in [0,1]:
            px = (sum(df['groundTruth']==i))/(len(df))
            py = (sum(df[x]==j))/(len(df))
            pxy = len(df[(df['groundTruth']==i) & (df[x]==j)])/len(df)
            if pxy==0: # Log 0 cannot happen
                if px*py==0:
                    pmi = math.log((pxy+0.0001)/(px*py+0.00001))
                else:
                    pmi = math.log((pxy+0.0001)/(px*py))
            else:
                pmi = math.log(pxy/(px*py))
            pmilist.append([i]+[j]+[px]+[py]+[pxy]+[pmi])
    pmidf = pd.DataFrame(pmilist)
    pmidf.columns = ['x','y','px','py','pxy','pmi']
    return pmidf

def pmiIndivCal(df, x, gt, label_column='groundTruth'):
    px = (sum(df[label_column]==gt))/(len(df))
    py = (sum(df[x]==1))/(len(df))
    pxy = len(df[(df[label_column]==gt) & (df[x]==1)])/len(df)

    if pxy==0: #Log 0 cannot happen
        if px*py==0:
            pmi = math.log((pxy+0.0001)/(px*py+0.00001))
        else:
            pmi = math.log((pxy+0.0001)/(px*py))
    else:
        pmi = math.log(pxy/(px*py))
    return pmi

# Compute PMI for all terms and all possible labels
def pmiForAllCal(df, topk, label_column='groundTruth'):
    #Try calculate all the pmi for top k and store them into one pmidf dataframe
    pmilist = []
    pmiposlist = []
    pmineglist = []
    for word in tqdm(topk):
        pmilist.append([word[0]]+[pmiCal(df,word[0])])
        pmiposlist.append([word[0]]+[pmiIndivCal(df,word[0],'positive',label_column)])
        pmineglist.append([word[0]]+[pmiIndivCal(df,word[0],'negative',label_column)])
    pmidf = pd.DataFrame(pmilist)
    pmiposlist = pd.DataFrame(pmiposlist)
    pmineglist = pd.DataFrame(pmineglist)
    pmiposlist.columns = ['word','pmi']
    pmineglist.columns = ['word','pmi']
    pmidf.columns = ['word','pmi']
    return pmiposlist, pmineglist, pmidf
```

(a) Pointwise Mutual Information (Word)

In [162]:

```
pmiposlist, pmineglist, pmidf = pmiForAllCal(finaldf,topk_word)
```

100%|██████████| 50/50 [00:00<00:00, 60.02it/s]

In [163]:

```
#Sorted top pmi words for positive reviews
pmiposlist.sort_values('pmi',ascending=0).head(5)
```

Out[163]:

	word	pmi
29	downtown	0.224852
47	quiet	0.221746
49	restaurants	0.217873
32	helpful	0.205863
4	great	0.202775

In [164]:

```
#Sorted top pmi words for negative reviews
pmineglist.sort_values('pmi',ascending=0).head(5)
```

Out[164]:

	word	pmi
48	door	0.603965
21	could	0.440010
25	get	0.376872
26	desk	0.373562
46	even	0.337345

Top positive rankings tell us the location is very important. Tourists like downtown hotels, and with quiet environment, good restaurants.

From top negative rankings we can see that most complaints are about facilities like door.

(b) Pointwise Mutual Information (Phrase)

In [165]:

```
pmiposlist_np, pmineglist_np, pmidf_np = pmiForAllCal(finaldf_np,topk_np)
```

100%|██████████| 50/50 [00:00<00:00, 63.95it/s]

In [166]:

```
pmiposlist_np.sort_values('pmi',ascending=0).head(10)
```

Out[166]:

	word	pmi
38	great stay	0.341763
43	whitney manor	0.338133
35	secret garden	0.333795
34	nice touch	0.302542
14	friendli staff	0.302542
21	kingston area	0.292973
22	minut drive	0.290212
11	great place	0.282502
2	downtown kingston	0.267072
4	comfort bed	0.257422

In [167]:

```
pmineglist_np.sort_values('pmi',ascending=0).head(10)
```

Out[167]:

	word	pmi
23	credit card	1.012474
29	first night	0.869752
17	holiday inn	0.724792
46	next day	0.694020
41	air condition	0.676002
48	breakfast room	0.666432
45	mini fridg	0.607009
42	ground floor	0.607009
1	comfort inn	0.591694
6	park lot	0.570641

Top positive rankings tell us that people like hotels that located in downtown and have friendly staff.

The top negative noun phrase is credit card. People may complain about the hotel when they have issue paying with credit card. And hotels with negative reivews often have facility problems(e.g. air condition not working).

(c) Repeat this analysis for the single top and single bottom hotel (according to the ground truth rating).

In [0]:

```
top_hotel = hotelRatingDfGt['hotelName'][:10].values
bot_hotel = hotelRatingDfGt['hotelName'][-5:].values
```

In [191]:

```
print('top hotel:',top_hotel[6])
print('bottom hotel:', bot_hotel[1])
```

```
top hotel: Best Western Fireside Inn
bottom hotel: Bayside Inn &amp;amp; Waterfront Suites
```

In [0]:

```
hotel_topdf=hotelDf[hotelDf['hotelName']==top_hotel[6]].reset_index()
hotel_botdf=hotelDf[hotelDf['hotelName']==bot_hotel[1]].reset_index()

topk_word_top=non_stopword(hotel_topdf,label='all')
finaldf_top= comprehensiveDf(hotel_topdf,topk_word_top,mode='word')
topk_word_topNP=NP_topk(hotel_topdf,label='all')
finaldf_topNP= comprehensiveDf(hotel_topdf,topk_word_topNP,mode='phrase')

topk_word_bot=non_stopword(hotel_botdf,label='all')
finaldf_bot= comprehensiveDf(hotel_botdf,topk_word_bot,mode='word')
topk_word_botNP=NP_topk(hotel_botdf,label='all')
finaldf_botNP= comprehensiveDf(hotel_botdf,topk_word_botNP,mode='phrase')
```

In [192]:

```
pmiposlist_top, pmineglist_top, pmidf_top = pmiForAllCal(finaldf_top,topk_word_top)
pmiposlist_bot, pmineglist_bot, pmidf_bot = pmiForAllCal(finaldf_bot,topk_word_bot)

pmiposlist_topPhrase, pmineglist_topPhrase, pmidf_topPhrase = pmiForAllCal(finaldf_topNP,topk_wo
rd_topNP)
pmiposlist_botPhrase, pmineglist_botPhrase, pmidf_botPhrase = pmiForAllCal(finaldf_botNP,topk_wo
rd_botNP)
```

```
100%|██████████| 50/50 [00:00<00:00, 96.33it/s]
100%|██████████| 50/50 [00:00<00:00, 97.86it/s]
100%|██████████| 50/50 [00:00<00:00, 96.27it/s]
100%|██████████| 50/50 [00:00<00:00, 92.62it/s]
```

In [193]:

```
pmiposlist_topPhrase.sort_values('pmi',ascending=0).head(5)
```

Out[193]:

	word	pmi
0	best western firesid inn	0.072571
22	fire place	0.072571
24	stuf anim	0.072571
26	night stay	0.072571
27	stori hotel	0.072571

In [194]:

```
pmineglist_topPhrase.sort_values('pmi',ascending=0).head(5)
```

Out[194]:

	word	pmi
29	unpleas experi femal worker	2.659260
44	nice experi	2.659260
5	breakfast room	2.253795
33	great breakfast	1.966113
34	hotel staff	1.966113

In [195]:

```
pmiposlist_botPhrase.sort_values('pmi',ascending=0).head(5)
```

Out[195]:

	word	pmi
41	conveni locat	1.014731
20	good stay	1.014731
18	standard room	1.014731
21	nice ladi	1.014731
16	friendli staff	1.014731

In [196]:

```
pmineglist_botPhrase.sort_values('pmi',ascending=0).head(5)
```

Out[196]:

	word	pmi
0	doubl bed	0.450201
24	mani hotel	0.450201
48	guy cur	0.450201
40	extra child	0.450201
39	previou guest	0.450201

From reviews of the top hotel Best Western Fireside Inn, we can see that people like its fire place and complain about the unpleasant hotel workers.

For the bottom hotel Bayside Inn & Waterfront Suites, people like its convenient location and friendly staff but complain about its facility like double bed, and maybe the bed is not tidy after previous guest leaving.

Q5. General Plots

(a) Histogram

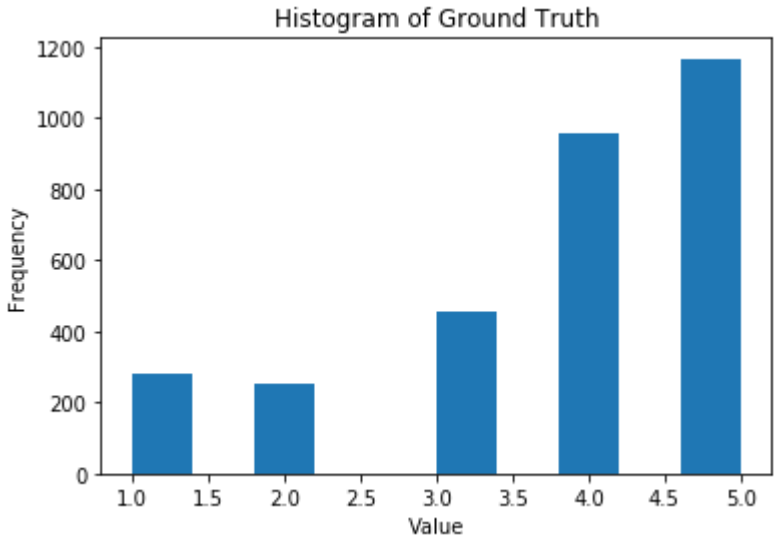
In [0]:

```
def getHistogram(compdf, measure, title):
    if measure=='both':
        x = [compdf['ratingScore'].values/5]
        y = [compdf['vader'].values]
        bins = np.linspace(-1, 1, 100)
        plt.title(title)
        plt.hist(x, bins, label='x')
        plt.hist(y, bins, label='y')
        plt.legend(loc='upper right')
        plt.show()

    else:
        plt.hist(compdf[measure].values)
        plt.title(title)
        plt.xlabel("Value")
        plt.ylabel("Frequency")
        fig = plt.gcf()
```

(a) Show separate histograms of ground truth and Vader sentiment scores (ignore hotel ID).

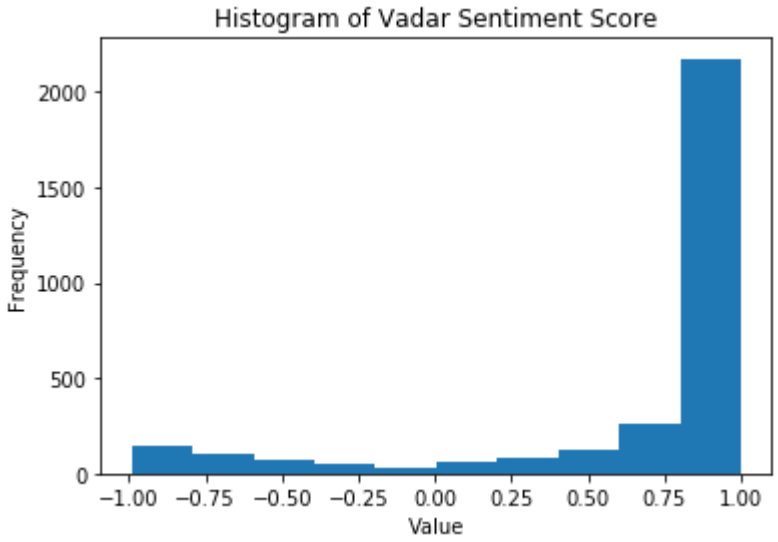
In [40]:

```
# (a) Show separate histograms of ground truth and Vader sentiment scores (ignore hotel ID).
getHistogram(hotelDf,'ratingScore', 'Histogram of Ground Truth')
```



In [41]:

```
getHistogram(hotelDf, 'vader', 'Histogram of Vadar Sentiment Score')
```



Both hisograms have more reviews on positive ratings. People are more likely to write a review about the hotel when they like this hotel.

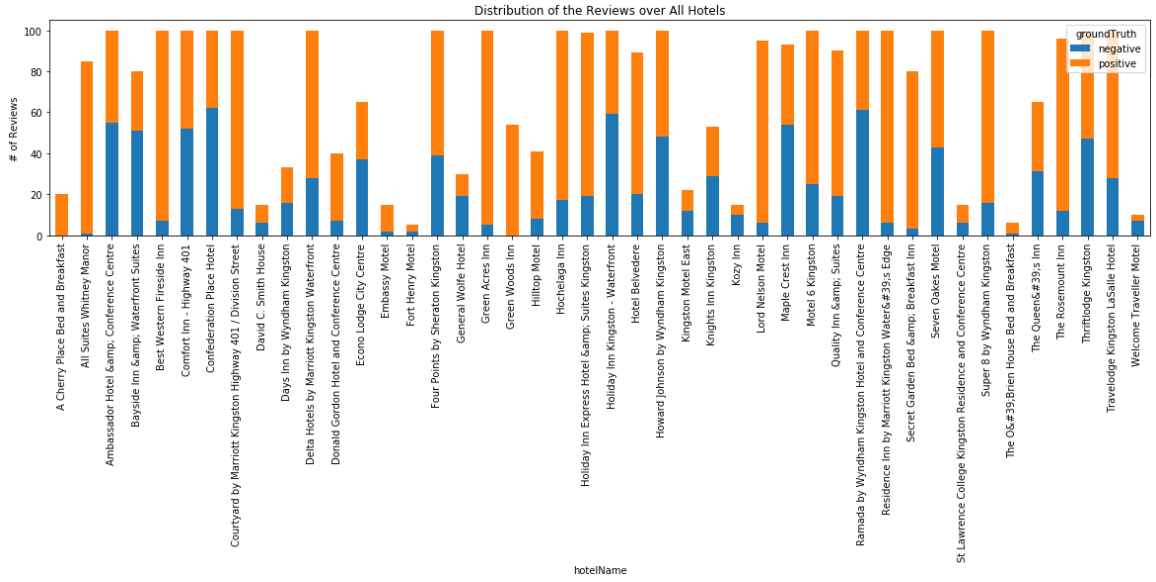
(b) Show a histogram of the number of reviews per hotel

In [42]:

```
review_hotel=hotelDf.groupby(['hotelName', 'groundTruth']).size().unstack('groundTruth').fillna(
0)
review_hotel.plot(kind='bar', stacked=True,figsize=(20,4))

plt.ylabel('# of Reviews')
plt.title('Distribution of the Reviews over All Hotels')
```

Out[42]:

```
Text(0.5, 1.0, 'Distribution of the Reviews over All Hotels')
```



Most hotels that have more than 60 reviews have more positive reviews than negative reviews.

(b) Boxplots

(a) 5 side-by-side boxplots for top-5 hotels

In [0]:

```
# review_num=hotelDf.groupby(['hotelName'])['vader'].count().rename('count').reset_index()
# review_num.sort_values('count',ascending=0)
```

In [159]:

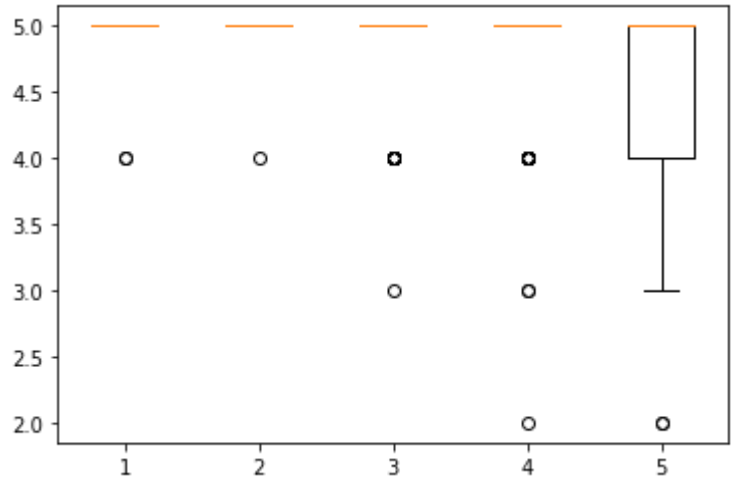
```
tp5gthotel = hotelRatingDfGt['hotelName'][:5].values
tp5gthotel
```

Out[159]:

```
array(['Green Woods Inn', 'A Cherry Place Bed and Breakfast',
       'All Suites Whitney Manor',
       'Secret Garden Bed &amp; Breakfast Inn', 'Green Acres Inn'],
      dtype=object)
```

In [44]:

```
#Plot top 5 side-by-side boxplot for top 5 ground truth rated hotel


greeenwood = hotelDf.loc[hotelDf['hotelName'] == tp5gthotel[0]]['ratingScore']
cherryplace = hotelDf.loc[hotelDf['hotelName'] == tp5gthotel[1]]['ratingScore']
whitneymanor = hotelDf.loc[hotelDf['hotelName'] == tp5gthotel[2]]['ratingScore']
secretgarden = hotelDf.loc[hotelDf['hotelName'] == tp5gthotel[3]]['ratingScore']
greenacres = hotelDf.loc[hotelDf['hotelName'] == tp5gthotel[4]]['ratingScore']

data = [greeenwood, cherryplace, whitneymanor, secretgarden, greenacres]
# multiple box plots on one figure
plt.figure()
plt.boxplot(data)
plt.show()
```



In [45]:

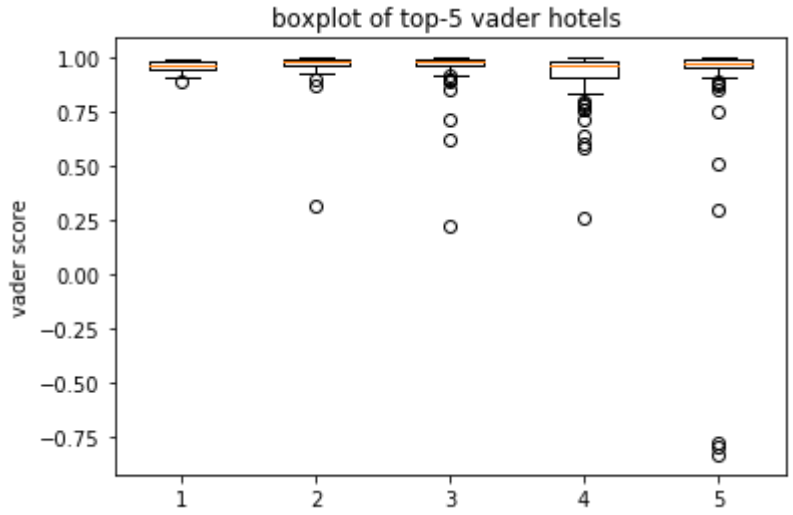
```
tp5gthotel_vd = hotelRatingDfVd['hotelName'][:5].values
tp5gthotel_vd
```

Out[45]:

```
array(['A Cherry Place Bed and Breakfast', 'Green Woods Inn',
       'Secret Garden Bed &amp;amp; Breakfast Inn', 'Green Acres Inn',
       'The Rosemount Inn'], dtype=object)
```

In [46]:

```
#Plot top 5 side-by-side boxplot for top 5 ground truth rated hotel


cherryplace = hotelDf.loc[hotelDf['hotelName'] == tp5gthotel_vd[0]]['vader']
greeenwood = hotelDf.loc[hotelDf['hotelName'] == tp5gthotel_vd[1]]['vader']
secretgarden = hotelDf.loc[hotelDf['hotelName'] == tp5gthotel_vd[2]]['vader']
greenacres = hotelDf.loc[hotelDf['hotelName'] == tp5gthotel_vd[3]]['vader']
rosemount = hotelDf.loc[hotelDf['hotelName'] == tp5gthotel_vd[4]]['vader']

data = [ cherryplace,greeenwood,  secretgarden, greenacres,rosemount ]
# multiple box plots on one figure
plt.figure()
plt.title('boxplot of top-5 vader hotels ')
plt.ylabel('vader score')
plt.boxplot(data)
plt.show()
```



(b) Report the mean and variance of the ground truth and Vader sentiment scores for the top-5 ranked hotels according to star rating.

In [47]:

```
# (b) The mean and variance of the ground truth for the top-5 ranked hotels according to star rating.
hotelReview_top5DF = hotelDf[hotelDf['hotelName'].isin(tp5gthotel.tolist())]
hotelReview_top5DF.groupby('hotelName').mean()[['ratingScore','vader']].sort_values('ratingScore',ascending=0)
```

Out[47]:

	ratingScore	vader
hotelName		
Green Woods Inn	4.962963	0.959917
A Cherry Place Bed and Breakfast	4.950000	0.960145
All Suites Whitney Manor	4.858824	0.881452
Secret Garden Bed & Breakfast Inn	4.762500	0.954265
Green Acres Inn	4.620000	0.926452

In [48]:

```
hotelReview_top5DF.groupby('hotelName').std()[['ratingScore','vader']].sort_values('ratingScore',ascending=1)
```

Out[48]:

	ratingScore	vader
hotelName		
Green Woods Inn	0.190626	0.092512
A Cherry Place Bed and Breakfast	0.223607	0.029599
All Suites Whitney Manor	0.382751	0.166969
Secret Garden Bed & Breakfast Inn	0.556748	0.099864
Green Acres Inn	0.647918	0.107320

(c)

Boxplot makes more sense since it excludes the outliers while variance consider outlier. Outliers may have large effect to the mean since the sample is small.

(c) Scatterplots and heatmaps

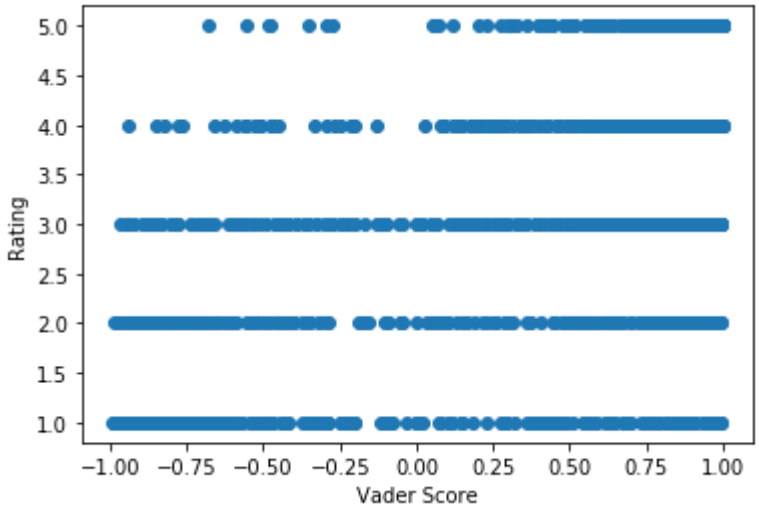
(a) Show the scatterplot of ground truth score (star rating) versus Vader sentiment score.

In [49]:

```
# (a) Show the scatterplot of ground truth score (star rating) versus Vader sentiment score.
y = hotelDf['ratingScore'].values
x = hotelDf['vader'].values
plt.plot(x, y,"o")
plt.ylabel('Rating')
plt.xlabel('Vader Score')
```

Out[49]:

Text(0.5, 0, 'Vader Score')

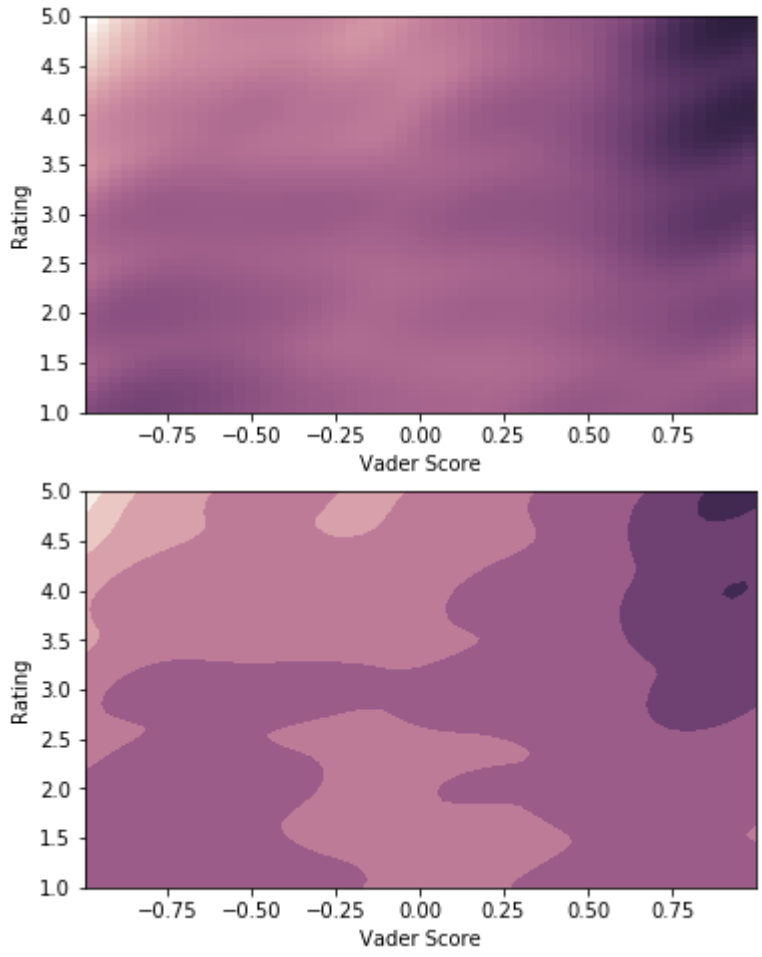


In [50]:

```
# Show the heatmap of ground truth score (star rating) versus Vader sentiment score.

from scipy.stats.kde import gaussian_kde

k = gaussian_kde(np.vstack([x, y]))
xi, yi = np.mgrid[x.min():x.max():x.size**0.5*1j,y.min():y.max():y.size**0.5*1j]
zi = k(np.vstack([xi.flatten(), yi.flatten()]))

cmap = sns.cubehelix_palette(light=1, as_cmap=True)
fig = plt.figure(figsize=(6,8))
ax1 = fig.add_subplot(211)
ax2 = fig.add_subplot(212)

ax1.pcolormesh(xi, yi, np.log10(zi.reshape(xi.shape)), cmap=cmap)
ax2.contourf(xi, yi, np.log10(zi.reshape(xi.shape)), cmap=cmap)

ax1.set_xlim(x.min(), x.max())
ax1.set_ylim(y.min(), y.max())
ax2.set_xlim(x.min(), x.max())
ax2.set_ylim(y.min(), y.max())

ax1.set_xlabel('Vader Score')
ax1.set_ylabel('Rating')

ax2.set_xlabel('Vader Score')
ax2.set_ylabel('Rating')
```

Out[50]:

Text(0, 0.5, 'Rating')



High rating(4-5) most likely corresponds to postive comment(the drak area on the top right). And we can see that with rating lower than 3.5, half of the comments are not nice while others are comparatively acceptable.

(b) Show scatterplots of the length of reviews versus each of ground truth score and Vader sentiment score.

In [0]:

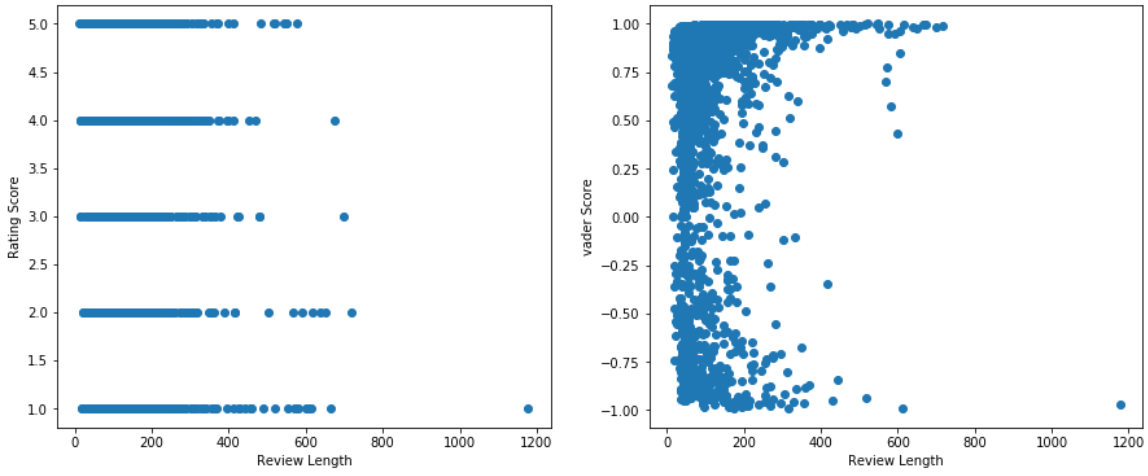
```
hotelDf['reviewLength'] = hotelDf['reviewColumn'].apply(lambda x:len(x.split()))
```

In [160]:

```
y = hotelDf['reviewLength'].values
x1 = hotelDf['ratingScore'].values
x2 = hotelDf['vader'].values

fig = plt.figure(figsize=(15,6))
ax1 = fig.add_subplot(121)
ax2 = fig.add_subplot(122)

ax1.plot( y,x1,"o")
ax2.plot( y,x2,"o")

ax1.set_ylabel('Rating Score')
ax1.set_xlabel('Review Length')

ax2.set_ylabel('vader Score')
ax2.set_xlabel('Review Length')
```

Out[160]:

Text(0.5, 0, 'Review Length')

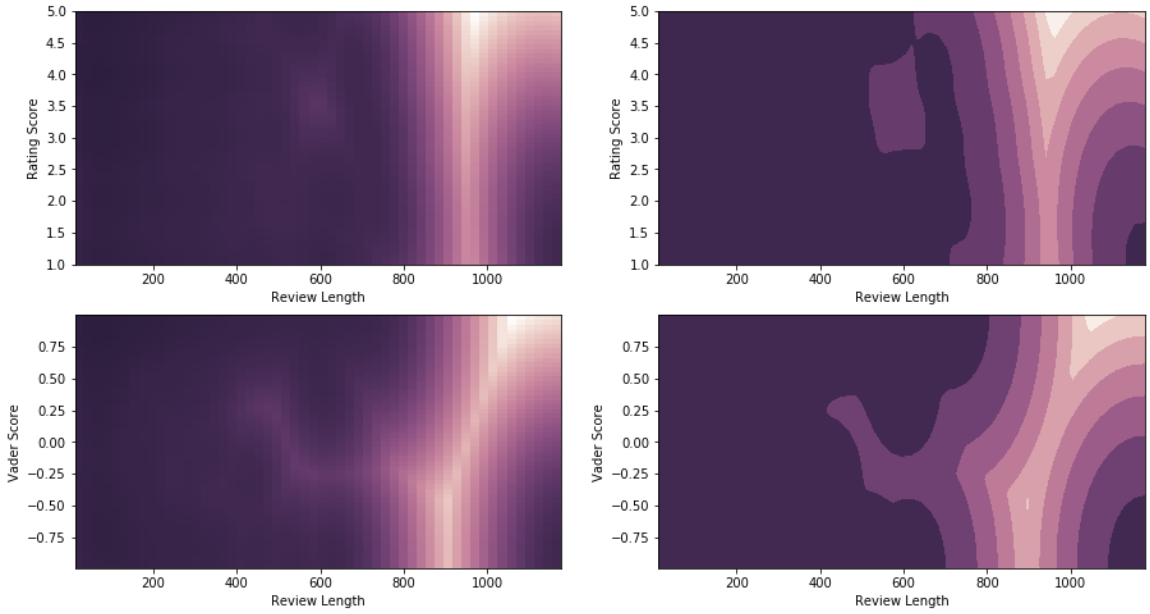


In [53]:

```
x = hotelDf['reviewLength'].values
y_vr = hotelDf['vader'].values
y=hotelDf['ratingScore'].values

kv = gaussian_kde(np.vstack([x, y_vr]))
xiv, yiv = np.mgrid[x.min():x.max():x.size**0.5*1j,y_vr.min():y_vr.max():y_vr.size**0.5*1j]
ziv = kv(np.vstack([xiv.flatten(), yiv.flatten()]))

k = gaussian_kde(np.vstack([x, y]))
xi, yi = np.mgrid[x.min():x.max():x.size**0.5*1j,y.min():y.max():y.size**0.5*1j]
zi = k(np.vstack([xi.flatten(), yi.flatten()]))
cmap = sns.cubehelix_palette(light=1, as_cmap=True)
fig = plt.figure(figsize=(15,8))
ax1 = fig.add_subplot(221)
ax2 = fig.add_subplot(222)
ax3 = fig.add_subplot(223)
ax4 = fig.add_subplot(224)

ax1.pcolormesh(xi, yi, np.log10(zi.reshape(xi.shape)), cmap=cmap)
ax2.contourf(xi, yi, np.log10(zi.reshape(xi.shape)), cmap=cmap)

ax3.pcolormesh(xiv, yiv, np.log10(ziv.reshape(xiv.shape)), cmap=cmap)
ax4.contourf(xiv, yiv, np.log10(ziv.reshape(xiv.shape)), cmap=cmap)

ax1.set_xlim(x.min(), x.max())
ax1.set_ylim(y.min(), y.max())
ax2.set_xlim(x.min(), x.max())
ax2.set_ylim(y.min(), y.max())
ax3.set_xlim(x.min(), x.max())
ax3.set_ylim(y_vr.min(), y_vr.max())
ax4.set_xlim(x.min(), x.max())
ax4.set_ylim(y_vr.min(), y_vr.max())

ax1.set_xlabel('Review Length')
ax1.set_ylabel('Rating Score')

ax2.set_xlabel('Review Length')
ax2.set_ylabel('Rating Score')

ax3.set_xlabel('Review Length')
ax3.set_ylabel('Vader Score')

ax4.set_xlabel('Review Length')
ax4.set_ylabel('Vader Score')
```

Out[53]:

Text(0, 0.5, 'Vader Score')



The scatter and heatmaps indicate that most positive and negative reviews are tend to have short review length. Some extremely negative reviews have very long review length.

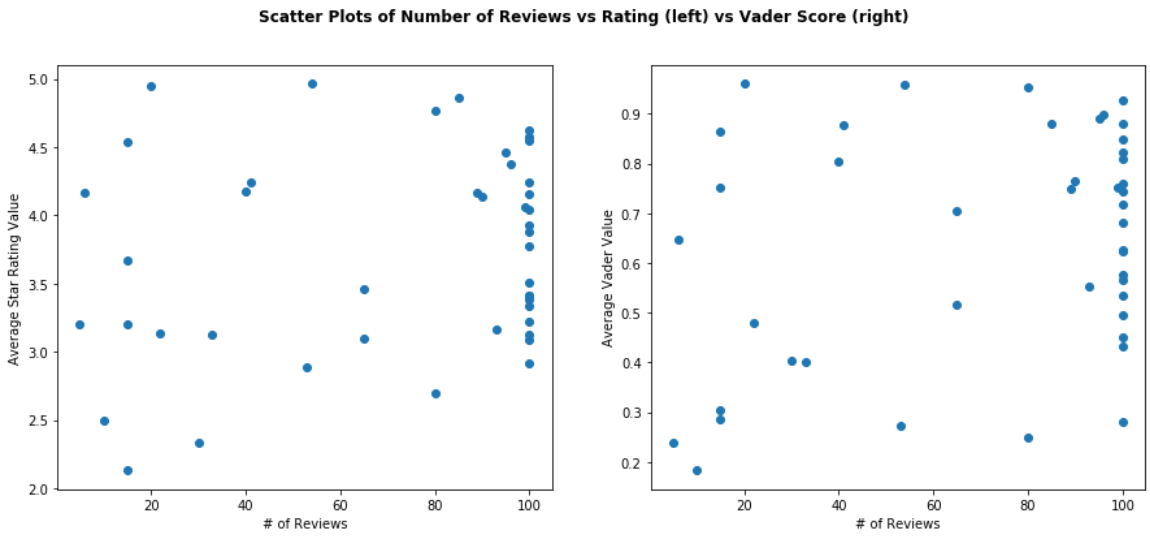
(c) Show two scatterplots of the number of reviews per hotel versus each of average ground truth score and average Vader sentiment score.

In [54]:

```
review_count = hotelDf.groupby('hotelName').size().tolist()

x = np.array(review_count)
y = hotelRatingDfGt.sort_values('hotelName',ascending=1)['avgRatingScore'].values
y_v = hotelRatingDfVd.sort_values('hotelName',ascending=1)['avgRatingScore'].values


fig = plt.figure(figsize=(15,6))
plt.suptitle('Scatter Plots of Number of Reviews vs Rating (left) vs Vader Score (right)', fontweight='bold')

ax1 = fig.add_subplot(121)
ax2 = fig.add_subplot(122)

ax1.plot(x, y,"o")
ax1.set_ylabel('Average Star Rating Value')
ax1.set_xlabel('# of Reviews')

ax2.plot(x, y_v,"o")
ax2.set_ylabel('Average Vader Value')
ax2.set_xlabel('# of Reviews')
```

Out[54]:

Text(0.5, 0, '# of Reviews')



It's hardly to see any trends from these two images. Some of the hotels with most reviews have positive reviews, others have negative reviews.